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Review Article

Recent Fuzzy Generalisations of Rough Sets Theory: A Systematic Review and Methodological Critique of the Literature

Abbas Mardani,[1] Mehrbakhsh Nilashi,[2,3] Jurgita Antucheviciene,[4] Madjid Tavana,[5,6] Romualdas Bausys,[7] and Othman Ibrahim[2]

[1] *Faculty of Management, Universiti Teknologi Malaysia (UTM), 81310 Skudai, Johor, Malaysia*
[2] *Faculty of Computing, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia*
[3] *Department of Computer Engineering, Lahijan Branch, Islamic Azad University, Lahijan, Iran*
[4] *Department of Construction Management and Real Estate, Vilnius Gediminas Technical University, Sauletekio Al. 11, LT-10223 Vilnius, Lithuania*
[5] *Business Systems and Analytics Department, La Salle University, Philadelphia, PA 19141, USA*
[6] *Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, 33098 Paderborn, Germany*
[7] *Department of Graphical Systems, Vilnius Gediminas Technical University, Saulėtekio Ave. 11, LT-10223 Vilnius, Lithuania*

Correspondence should be addressed to Jurgita Antucheviciene; jurgita.antucheviciene@vgtu.lt

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Rough set theory has been used extensively in fields of complexity, cognitive sciences, and artificial intelligence, especially in numerous fields such as expert systems, knowledge discovery, information system, inductive reasoning, intelligent systems, data mining, pattern recognition, decision-making, and machine learning. Rough sets models, which have been recently proposed, are developed applying the different fuzzy generalisations. Currently, there is not a systematic literature review and classification of these new generalisations about rough set models. Therefore, in this review study, the attempt is made to provide a comprehensive systematic review of methodologies and applications of recent generalisations discussed in the area of fuzzy-rough set theory. On this subject, the Web of Science database has been chosen to select the relevant papers. Accordingly, the systematic and meta-analysis approach, which is called "PRISMA," has been proposed and the selected articles were classified based on the author and year of publication, author nationalities, application field, type of study, study category, study contribution, and journal in which the articles have appeared. Based on the results of this review, we found that there are many challenging issues related to the different application area of fuzzy-rough set theory which can motivate future research studies.

1. Introduction

Rough set theory is a powerful and popular machine learning method [1]. It is particularly appropriate for dealing with information systems that exhibit inconsistencies [2]. Fuzzy-rough set theory can be integrated with the rough set theory to handle data with continuous attributes and can detect inconsistencies in the data. Because the fuzzy-rough set model is a powerful tool in analysing inconsistent and vague data, it has proven to be very useful in many application areas. Rough set theory, introduced by Pawlak [3] in the 1980s, is a powerful machine learning tool that has applications in many data mining [4–11] instances, attribute and feature selection [12–25], and data prediction [26, 27]. Rough set theory deals with information systems that contain inconsistent data, such as two patients who have the same symptoms but different diseases. In the rough set analysis, data is expected to be discrete. Therefore, a continuous numeric attribute is required to be discretized. Fuzzy-rough set theory [28] is an extension of the rough set theory that deals with continuous numerical attributes. It can solve the same problems that rough set can solve and also can handle both numerical and discrete data. The importance of fuzzy-rough set theory is clearly seen in several applications areas. For example, Wang [29] and Wang [30] investigated topological characterizations of generalised fuzzy-rough sets in the context of basic rough equalities. Pan et al. [31] enhanced the fuzzy preference relation rough set model with an additive consistent fuzzy preference relation. Namburu et al. [32] suggested the soft fuzzy-rough set-based magnetic resonance brain image segmentation for handling the uncertainty related to indiscernibility and vagueness. Li et al. [33] proposed an effective fuzzy-rough set model for feature selection. Feng et al. [34] used uncertainty measures for reduction of multigranulation based on fuzzy-rough sets, avoiding the negative and positive regions. Sun et al. [35] presented three kinds of multigranulation fuzzy-rough sets over two universes using a constructive method. Zhao and Hu [36] examined a decision-theoretic rough set model in the context of models of interval-valued fuzzy and fuzzy probabilistic approximation spaces. Zhang and Shu [37] suggested a new paradigm based on generalised interval-valued fuzzy-rough sets by combining the theory of rough sets and theory of interval-valued fuzzy sets based on axiomatic and constructive methods. Zhang et al. [24] proposed a new fuzzy-rough set theory based on information entropy for feature selection. Wang and Hu [38] proposed arbitrary fuzzy relations by integrating granular variable precision fuzzy-rough sets and general fuzzy relations. Vluymans et al. [19] suggested a new kind of classifier for imbalanced multi-instance data based on fuzzy-rough set theory. Feng and Mi [39] investigated and reviewed the variable precision of multigranulation fuzzy decision-theoretic rough sets in an information system. Wang and Hu [40] presented novel generalised L-fuzzy-rough sets for generalisation of the notion of L-fuzzy-rough sets.

In recent decades, various kinds of models have been proposed and developed regarding the fuzzy generalisation of rough set theory. However, the literature review has not kept pace with the rapid addition of knowledge in this field. Therefore, we believe that there is a need for a systematic consideration of the most relevant recent studies conducted in this area. This review paper attempts to systematically review the previous studies that proposed or developed fuzzy-rough sets theory. This review paper adds significant insight into the literature of fuzzy-rough set theory, by considering some new perspectives in examining the articles, such as the classification of the papers based on author and year of publication, author nationalities, application field, type of study, study category, study contribution, and the journals in which they appear.

The structure of this review study is organised as follows. Section 2 shortly reviews the literature regarding fuzzy logic and fuzzy sets, rough sets, fuzzy set theory, fuzzy logical operators, fuzzy relations, rough set theory, and fuzzy-rough set theory. In Section 3, we present the related works. Section 4 presents research methodology including the systematic review, meta-analysis, and the procedures of this study. Section 5 provides findings of this review based on the application areas. Section 6 presents the distribution of papers by the journals. In Section 7, we present the distribution of papers by the year of publication. Section 8 presents the distribution of papers based on the nationality of authors. Section 9 discusses the results of this review with the focus on the recent fuzzy generalisation of rough sets theory and further investigations in this area. Finally, Section 10 presents the conclusion, limitations, and recommendations for future studies.

2. Fuzzy-Rough Sets Theory

2.1. Fuzzy Logic and Fuzzy Sets. Binary logic is discrete and has only two logic values which are true and false, that is, 1 and 0. In real-life, however, things are true to some extent. For example, regarding the patient there are some assumptions such as patient is sick, or say patient is very sick or starting to become sick. Therefore, we cannot confidently say if the patient is sick or not with a certain intensity. Fuzzy logic [43] has extended binary logic through adding an intensity range of values to specify the extent to which something is true. In this situation, the range of truth values is between 0 and 1. The closer the truth value of a statement to 1, the truer the statement. For example, the patient is very sick could have the degree of sickness around 0.9 to specify that the patient is very sick. On the other side, patient could have the sickness degree of 0.1 indicating that the patient is nearly recovered from the illness. A fuzzy set [44] is a set of factors that fit to the set with the membership degree. For instant, we assume that there are two fuzzy sets representing two groups of people including old and young people. Thus the larger the age of one person, the higher the membership degree to the old people, and the lower the person membership degree to the young people. Meanwhile fuzzy logic is extending the binary logic and moreover extends its logical operations. These are the t-conorm fuzzy logical t-norm and implicator [45] that extend the binary logical implication conjunction and disjunction.

2.2. Rough Sets. In the very big datasets with several items, calculating the gradual indiscernibility relation is very challenging in terms of memory and runtime. Rough set theory (Pawlak [46], Polkowski et al. [47]) is the novel mathematics technique dealing with uncertain and inexact knowledge in several applications in various real-life fields such as information analysis, medicine, and data mining. Rough set is the powerful machine learning technique which has been used in many application areas such as feature selection, prediction, instance selection, and decision-making. Rough set also has applications in many areas such as medical data analysis, image processing, finance, and many other real-life problems [3]. A rough set approximates a certain set of factors with two subsets including upper approximations and lower approximations. The fuzzy-rough set theory is constructed based on two theories including rough set theory and fuzzy set theory. In the next section, we present these theories with hybridisation of both theories.

2.3. Fuzzy Set Theory. Zadeh [44] found that traditional crisp set is not capable of explaining the whole thing in the real manner. Zadeh proposed fuzzy sets to solve this problem. Therefore Zadeh proposed a fuzzy set A as a mapping from the universe U to the interval $[0,1]$. The set $A(x)$ for $x \in U$ is called the degree of membership of x in A. Employ this method; factors in the universe could belong to a set to a certain degree. Discovery for the good fuzzy set for model concepts could be subjective and challenging; however it is more significant than trying to create an artificial crisp distinction among factors. Indeed that fuzzy set was an extension of crisp set. Consequently, any crisp set A could be modelled using a fuzzy set as follows:

$$\forall x \in U : A_{(x)} = \begin{cases} 1 \\ 0 \end{cases}$$
$$\forall x \in U : A_{(x)} = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{else.} \end{cases} \tag{1}$$

The cardinality of a fuzzy set A is defined as the sum of the membership values of all factors in the universe to A:

$$|A| = \sum_{x \in U} A_{(x)}. \tag{2}$$

2.4. Fuzzy Logical Operators. There is need for the new logical operators to extend the crisp sets to the fuzzy sets. In crisp set theory, for example, the proposition a factor belongs to the sets A and B is either true or false. For extending this theorem to fuzzy set theory, there is need to the fuzzy logical operators for extending the logical conjunction $\wedge$, for expressing to what extent an example x belongs to A and B, given the membership degrees $A(x)$ and $B(x)$.

The conjunction $\wedge$ and the disjunction $\vee$ were extended by using the t-conorm $\mathcal{S}$ and t-norm $\mathcal{T}$ that map $\mathcal{T}, S : [0,1]^2 \to [0,1]$, satisfying the following conditions:

$\mathcal{T}$ and $\mathcal{S}$ are increasing in both arguments.

$\mathcal{T}$ and $\mathcal{S}$ are commutative.

$\mathcal{T}$ and $\mathcal{S}$ are associative.

$$\forall x \in U : \mathcal{T}(x,1) = x,$$
$$\forall x \in U : \delta(x,0) = x. \tag{3}$$

The most significant examples of t-norms are the minimum operator τ_M, which is the largest t-norm, the product operator $\mathcal{T}_P$, and the Łukasiewicz t-norm $\mathcal{T}_L$:

$$\forall x, y \in (0,1) : \mathcal{T}_M(x,y) = \min(x,y)$$
$$\forall x, y \in (0,1) : \mathcal{T}_P(x,y) = xy \tag{4}$$
$$\forall x, y \in (0,1) : \mathcal{T}_L(x,y) = \max(0, x+y-1).$$

The important examples of t-conorms are the maximum operator $\mathcal{S}_M$, which is the smallest t-conorm, the probabilistic sum $\mathcal{S}_p$, and the Łukasiewicz t-conorm $\mathcal{S}_L$:

$$\forall x, y \in (0,1) : \mathcal{S}_M(x,y) = \max(x,y)$$
$$\forall x, y \in (0,1) : \mathcal{S}_p(x,y) = x+y-xy \tag{5}$$
$$\forall x, y \in (0,1) : \mathcal{S}_L(x,y) = \min(1, x+y).$$

The implication $\to$ is extended by fuzzy implicators, which are mappings $\mathfrak{T}\colon [0,1]^2 \to [0,1]$ that satisfy the following:

L is decreasing in the first and increasing in the second argument.

L satisfies $L(1,1) = L(0,0) = 1$ and $L(1,0) = 0$.

The well-knowing implicator is the Łukasiewicz implicator L_L, defined by

$$\forall x, y \in (0,1) : L_L(x,y) = \min(1, 1-x+y). \tag{6}$$

2.5. Fuzzy Relations. The binary fuzzy relations in U are the special type of fuzzy sets which are fuzzy sets R in U^2 and express to what extent x and y are associated with others. In the field of fuzzy-rough set, usually use relations for modelling indiscernibility between the examples. Therefore, we refer to them as indiscernibility relations. We need R to be minimum a fuzzy tolerance relation; that is, R is reflexive: $\forall x \in U$, $R(x,x) = 1$ and symmetric $\forall x, y \in U$, $R(x,y) = R(y,x)$.

These two situations are linked to the symmetry and reflexivity conditions of the equivalence relation. The third situation for an equivalence relation, transitivity, is translated to $\mathcal{T}$-transitivity for a certain t-norm $\mathcal{T}$:

$$\forall x, y, z \in \mathcal{T}(R(x,y), R(y,z)) \leq R(x,z). \tag{7}$$

For this case, R is called a $\mathcal{T}$-similarity relation. Thus when R is $\mathcal{T}_M$-transitive, R is $\mathcal{T}$-transitive for all t-norms $\mathcal{T}$. For this case, R will be a similarity relation.

2.6. Rough Set Theory. Pawlak [3] proposed the rough set theory for handling the problem of incomplete information. Pawlak introduced a universe U involving factors, an equivalence relation R on U, and a concept $A \subseteq U$ within the universe. The problem of incomplete information indicates that it should not be possible to determine the concept A based on the equivalence relation R, which is there are two factors x and y in U that are equivalent to R but to which x belongs to A and y does not. Figure 1 represented this case in which the universe is divided into squares applying the equivalence relation. The concept A does not follow the lines of the squares, which means that A cannot be described using R. In real world this kind of problem with incomplete information often occurs such as problem of spam classification. For example we assume the world contains nonspam and spam e-mails and mention that this concept is spam. The equivalence relation is introduced according to the predefined list of 10 words which usually are in the spam e-mails; thus it can mention that two e-mails are equivalent if they have the similar words among the list of 10 words. Some equivalence classes will be completely contained in the spam group, and some will be completely contained in the nonspam group. Though it is very likely that there are two e-mails that have the similar words among the list of 10 words, however for which one is spam and the other is nonspam. In this case, the equivalence relation is not

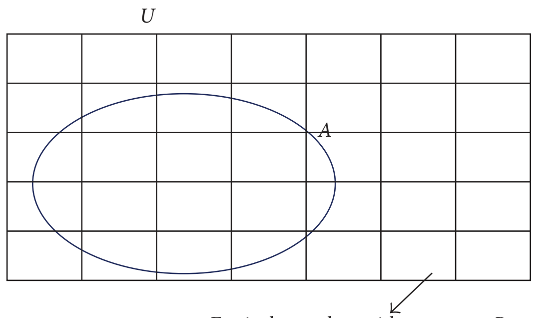


Figure 1: A universe U partitioned by an equivalence relation R and a concept $A \subseteq U$ that cannot be defined using R [41, 42].

able to distinguish between spam and nonspam. Pawlak [3] addressed this kind of problem by approximating the concept A. The lower approximation includes all the equivalence classes that are included in A, and the upper approximation includes the equivalence classes for which at least one factor is in A. Figure 2 represented the concept of lower and upper approximations.

An equivalence relation is reflexive; thus x is only included in $R \downarrow A$ if $x \in A$. The upper approximation is defined by

$$R \uparrow A = \left\{x \in U \mid \exists_y \in U : (x, y) \in R \wedge y \in A\right\}. \quad (8)$$

The lower approximation of A using R is defined as follows:

$$R \downarrow y = \{x \in U \mid \forall y \in U : (x, y) \in R \longrightarrow y \in A\}. \quad (9)$$

The lower approximation in the spam example contains all e-mails that are spam and for which all e-mails indiscernible from it are also spam. The upper approximation contains of e-mails that are spam and e-mails that are nonspam but for which there exists an e-mail indiscernible from it that is spam.

2.7. Fuzzy-Rough Set Theory. Fuzzy set theory enables us to model vague information, while rough set theory models incomplete information. These two theories are not competing, but rather complement each other. Many models have been proposed to hybridise rough sets and fuzzy sets [6, 29, 30, 34, 39, 170–178]. A fuzzy-rough set is the pair of lower and upper approximations of a fuzzy set A in a universe U on which a fuzzy relation R is defined. The fuzzy-rough model is obtained by fuzzifying the definitions of the crisp lower and upper approximation. Recall that the condition for an element $x \in U$ to belong to the crisp lower approximation is

$$\forall y \in U \, (x, y) \in R \longrightarrow y \in A. \quad (10)$$

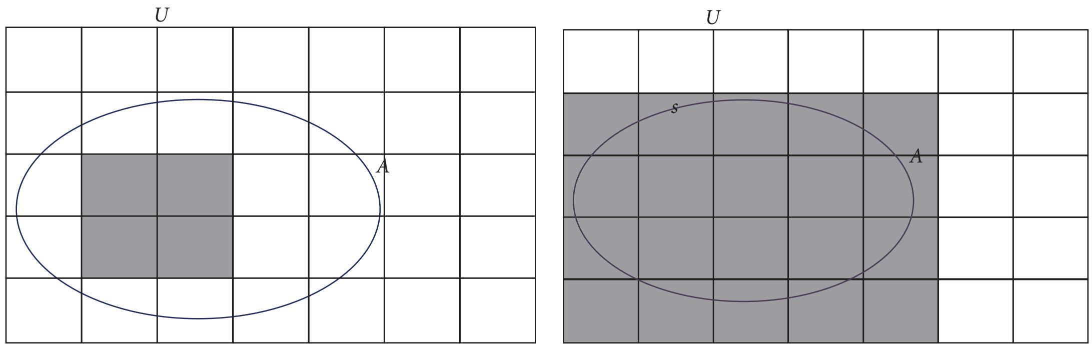
The equivalence relation R is now a fuzzy relation, and A is a fuzzy set. The values $R(x; y)$ and $A(y)$ are connected by a fuzzy implication $\mathscr{L}$, so $\mathscr{L}(R(x; y), A(y))$ expresses to what extent elements that are similar to x belong to A. The membership value of an element $x \in U$ to the lower approximation is high if these values $\mathscr{L}(R(x; y), A(y))$ are high for all $y \in A$:

$$\begin{aligned} &\forall x \in U \, (R \downarrow A)(x) = \min_{y \in U} \mathscr{L}(R(x, y), A(y)). \\ &\forall x \in U \, (R \uparrow A)(x) = \max_{y \in U} \mathscr{T}(R(x, y), A(y)). \end{aligned} \quad (11)$$

This upper approximation expresses to what extent there exist instances that are similar to x and belong to A.

3. Related Works

Morsi and Yakout [179] examined the relationship between fuzzy-rough sets theory based on R-implicators and left-continuous t-norms, with focus on fuzzy similarity in the axiomatic approach. Wang and Hong [180] proposed an algorithm to produce a set of fuzzy rules from noisy quantitative training data, by applying the variable precision rough set model. Molodtsov [181] employed the theory of rough sets in several ways and formulated the soft number notions, soft integral and soft derivative. Maji et al. [182] examined the soft sets in detail and provided the application of soft sets in decision-making by employing the rough sets reduction. Radzikowska and Kerre [28] investigated the family of fuzzy-rough sets based on fuzzy implicators, which were called generalised fuzzy-rough sets. De Cock et al. [183] introduced fuzzy-rough sets based on R-foresets of all objects with respect to a fuzzy binary relation, when R is a fuzzy serial relation. Jensen and Shen [184] proposed classical rough sets based on a dependency function of fuzzy-rough sets and presented the new greedy algorithm for reduction of redundant attributes. Mieszkowicz-Rolka and Rolka [185] proposed an approach based on the variable precision fuzzy-rough set approach to the analysis of noisy data. Mi and Zhang [186] introduced a new fuzzy-rough set definition based on a residual implication, θ and its dual, σ. Shen and Jensen [187] proposed an approach that integrates a fuzzy rule induction algorithm with a fuzzy-rough method for feature selection. Wu et al. [188] examined generalised fuzzy-rough sets in the axiomatic method. Bhatt and Gopal [189] proposed a new concept of compact computational domain for Jensen's algorithm for enhancing computational efficiency. Yeung et al. [190] proposed some fuzzy-rough set models by means of arbitrary fuzzy relations and investigated the connections between the existing fuzzy-rough sets. Deng et al. [191] investigated fuzzy relations by involving a fuzzy covering. Li and Ma [192] proposed two pairs of fuzzy-rough approximation operators, including fuzzy and crisp covering-based fuzzy-rough approximation operators. Aktaş and Çağman [193] compared the concepts of rough sets, soft sets, and fuzzy sets and showed that, for each fuzzy set, rough set is a soft set. Greco et al. [194] integrated the DTRS approach with the dominance-based rough set approach and presented a new generalised rough set theory approach. Cornelis et al. [195] introduced a classical rough set approach by utilising fuzzy tolerance relations, considering fuzzy-rough set theory. Wang et al. [196] introduced new definitions of fuzzy lower



(a) The lower approximation (b) The upper approximation

Figure 2: The concept A is approximated by means of the lower and upper approximations [41, 42].

and upper approximations by using the similarity between two objects. Hu et al. [197] proposed a novel fuzzy-rough set model, based on which a straightforward and efficient hybrid attribute reduction algorithm was designed. Lingras et al. [198] and Lingras et al. [199] applied the DTRS theory for clustering analysis. She and Wang [200] investigated L-fuzzy-rough set theory from an axiomatic method. Zhao et al. [201] suggested the new concept based on fuzzy variable precision rough sets for handling the noise of perturbation and misclassification. Wu et al. [202] introduced a new attribute reduction approach, focusing on the interval type 2 fuzzy-rough set model and providing some properties of interval type 2 fuzzy-rough sets. Yan et al. [203] proposed generalising the rough set model with fuzzy relation on two universes using fuzzy theory and probabilistic methods. Yang and Yao [204] investigated the multiagent DTRS model. Xu et al. [205] examined the GRS approach based on the rough membership function. Xia and Xu [206] investigated intuitionistic fuzzy information changing. Wu [207] examined fuzzy-rough sets based on t-norms and discussed algebraic structures and fuzzy topologies. Feng et al. [208] suggested the soft rough sets concept instead of equivalence classes and defined the parameterized soft set of upper and lower approximations. Meng et al. [209] suggested an approach for calculating the upper and lower approximations for fuzzy soft sets which efficiently define the boundary. Li and Zhou [210] and Li et al. [211] suggested a multiperspective explanation of the decision-theoretic rough set approach and attribute reduction. Jia et al. [212] investigated the problem related to attribute reduction for decision-theoretic rough set theory. Liu et al. [213] and Liu et al. [214] explored multiple-category classification with the DTRS method and applications in management science. Degang et al. [215] introduced a novel approach to examine fuzzy-rough sets by integrating granular computing. Hu et al. [94] used kernel functions for introducing the fuzzy similarity relations and developed the greedy algorithm based on dimensionality reduction. Ma and Sun [216] proposed a probabilistic rough set model on two universes. Ma and Sun [217] investigated the decision-theoretic rough set theory over two universes, based on the idea of classical DTRS theory. Liu et al. [218] studied the GRS approach based on two universes and discussed its properties. Chen et al. [102] used fuzzy-rough sets to present a matrix of fuzzy discernibility. Zhang et al. [111] proposed a general framework of intuitionistic fuzzy-rough sets and discussed the intuitionistic fuzzy operator and the properties of the model with the dual domain case. Wei et al. [219] investigated the relationships among rough approximations of fuzzy-rough set models. Chen et al. [117] explored the interpretation of several types of membership functions, geometrically, by using the lower approximations in fuzzy-rough sets, in terms of square distances in Krein spaces. Ma and Hu [220] examined lattice structures and the topology of L-fuzzy-rough sets by considering upper and lower approximations sets. Yang et al. [70] suggested a fuzzy probabilistic rough set model on two universes. Liang et al. [59] examined information retrieval and filtering by employing the DTRS theory. Zhang and Miao [221] and Zhang and Miao [222] proposed the double-quantitative approximation space for presenting two double-quantitative rough set theories. Yao et al. [101] suggested the variable precision (θ, σ)-fuzzy-rough sets theory regarding fuzzy granules. Liu et al. [223] investigated logistic regression for classification based on decision-theoretic rough sets theory. Ma et al. [224] suggested a decision region distribution preservation reduction in decision-theoretic rough set theory. Qian et al. [225] investigated the multigranulation decision-theoretic rough set approach. Sun et al. [82] examined the DTRFS application and model. Zhang and Miao [226] constructed a fundamental reduction framework for two-category decision-theoretic rough sets. Gong and Zhang [105] investigated a method of intuitionistic fuzzy sets and variable precision rough sets, to construct an extended intuitionistic fuzzy-rough set model. Zhao and Xiao [131] defined the general type-2 fuzzy-rough sets and discussed the basic properties of lower and upper approximation operators. Zhang and Miao [227] and Zhang and Miao [228] examined attribute reduction for proposing rough set theory models. D'eer et al. [118] investigated the drawbacks and benefits of implicator–conjunctor-based noise-tolerant fuzzy-rough set models. Li and Cui [77] studied the characterizations of the topology of fuzzy-rough sets by considering the similarity of fuzzy relations. Li and Cui [229] investigated fuzzy topologies considering a lower fuzzy-rough approximation operator based on the t-conorm. Xu et al. [230] introduced a knowledge reduction approach in a generalised approximation space over two universes. Li and

Xu [231] introduced the multigranulation decision-theoretic rough set approach in the ordered information system. Liang et al. [232] suggested three-way decisions by extending the DTRS approach to a qualitative environment. Ju et al. [233] presented a moderate attribute reduction model in DTRS. Li and Xu [234] investigated the double-quantitative DTRS approach based on assembling the upper and lower approximations of the GRS and DTRS methods. Wang [114] examined type 2 fuzzy-rough sets by considering two finite universes and utilising axiomatic and constructive methods and investigated some topological properties of type 2 fuzzy-rough sets. Zhang and Min [235] used three-way decisions regarding recommender systems. Wang [114] defined an upper approximation number for developing a quantitative analysis of covering-based rough set theory. Wang et al. [25] proposed a fitting fuzzy-rough set model to conduct feature selection. Yang and Hu [178] proposed a definition of fuzzy β-covering approximation spaces by introducing some new definitions of fuzzy β-covering approximation spaces, Ma's fuzzy covering-based rough set and the properties of fuzzy β-covering approximation spaces. Wang [29] investigated characterizations of generalised fuzzy-rough sets in the core rough equalities context. Namburu et al. [32] suggested a soft fuzzy-rough set-based segmentation of magnetic resonance brain image for handling the uncertainty regarding the indiscernibility and vagueness in a parameterized representation. Wang [30] examined the topological structures of L-fuzzy-rough set theory. Liang et al. [232] examined triangular fuzzy decision-theoretic rough sets. Zhang and Yao [236] examined functions of the Gini objective for three-way classification. Sun et al. [237] explored three-way group decision-making by using multigranulation fuzzy decision-theoretic rough sets. Feng et al. [34] investigated reduction of the multigranulation fuzzy information system based on uncertainty measures by considering variable precision multigranulation decision-theoretic fuzzy-rough set theory and avoiding the changing of negative region and positive region to small ones. Sun et al. [62] proposed the new fuzzy-rough set on a probabilistic approximation space and used it with respect to decision-making in unconventional emergency management. Hu et al. [171] proposed a new incremental method to update approximations of fuzzy information system over two universes. Fan et al. [72] introduced several double-quantitative DTRS (DQ-DTRFS) models based on logical conjunction and disjunction operations. Qiao and Hu [238] proposed a granular variable precision L-fuzzy-rough set theory based on residuated lattices with arbitrary L-fuzzy relations. Liang et al. [172] examined the decision principles of three-way decision rules based on the variation of loss functions with IFSs.

4. Research Method

For the research methodology in this study, we used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) provided by Moher et al. [239]. PRISMA has two main parts, including systematic reviews and meta-analyses. Systematic reviews provide objective summaries of what has been written and found out about research topics. This is especially valuable in wide research areas, where many publications exist, each focusing on a narrow aspect of the field [240]. Systematic reviews aim to provide a full overview of research conducted in a specific area until the present date. All research procedures have to be made explicit before the actual behaviour of the review to make the process objective and replicable. Meta-analysis provides a means of mathematically integrating findings employing diverse statistical approaches to study the diversity of the articles. In this kind of synthesis, original studies that are compatible with their quality level are selected. This aspect may help and highlight different facts which individual primary studies fail to do, for example, it may prove that results are statistically significant and relevant when small primary studies provide inconclusive and uncertain results with a large confidence interval [241]. The main goal of PRISMA is to help the researchers and practitioners complete a comprehensive and clear literature review [242].

Several previous studies have been conducted using PRISMA in the various fields to develop a comprehensive literature review [242–244]. In order to implement the PRISMA method in this study, we accomplish three main steps including literature search, choosing the eligible published papers, and extraction of data and summarising [237].

4.1. Literature Search. In this step, we have chosen the Web of Science database to provide a comprehensive application of fuzzy-rough set theories. The literature search was accomplished based on two keywords including rough set theories and fuzzy-rough set theories. We attempted to collect the current published papers from 2010 to 2016. In the first step of our search, we found 5648 scholarly papers related to the rough set theories and fuzzy-rough set theories which were extracted according to our strategy search. In the next step, we searched to find the papers which were published between 2010 and 2016 and checked the duplicate papers with redundant information. After this step, 296 papers were remaining. After removing 17 records due to duplication, we screened papers based on the titles and abstracts, and irrelevant papers were removed. In total, 193 potentially related papers remained (see Figure 3).

4.2. Articles Eligibility. In this step of the review, for the purpose of eligibility, we reviewed the full text of each article independently (which extracted from the last step). In the last step, we carefully identified the related articles to attain a consensus. Book chapters, unpublished working papers, editorial notes, master dissertations and doctoral theses, textbooks, and non-English papers were excluded. In the end, we selected 132 articles related to the fuzzy-rough sets, from 28 international scholarly journals between 2010 and 2016, which met our inclusion criteria. We selected the papers from 2010, because of such a large number of papers published in this field.

4.3. Data Extraction and Summarising. In the final step of our methodology, after negotiation with other authors, some required information was collected, and, finally, 132 articles were reviewed and summarised. In Table 1, all the selected

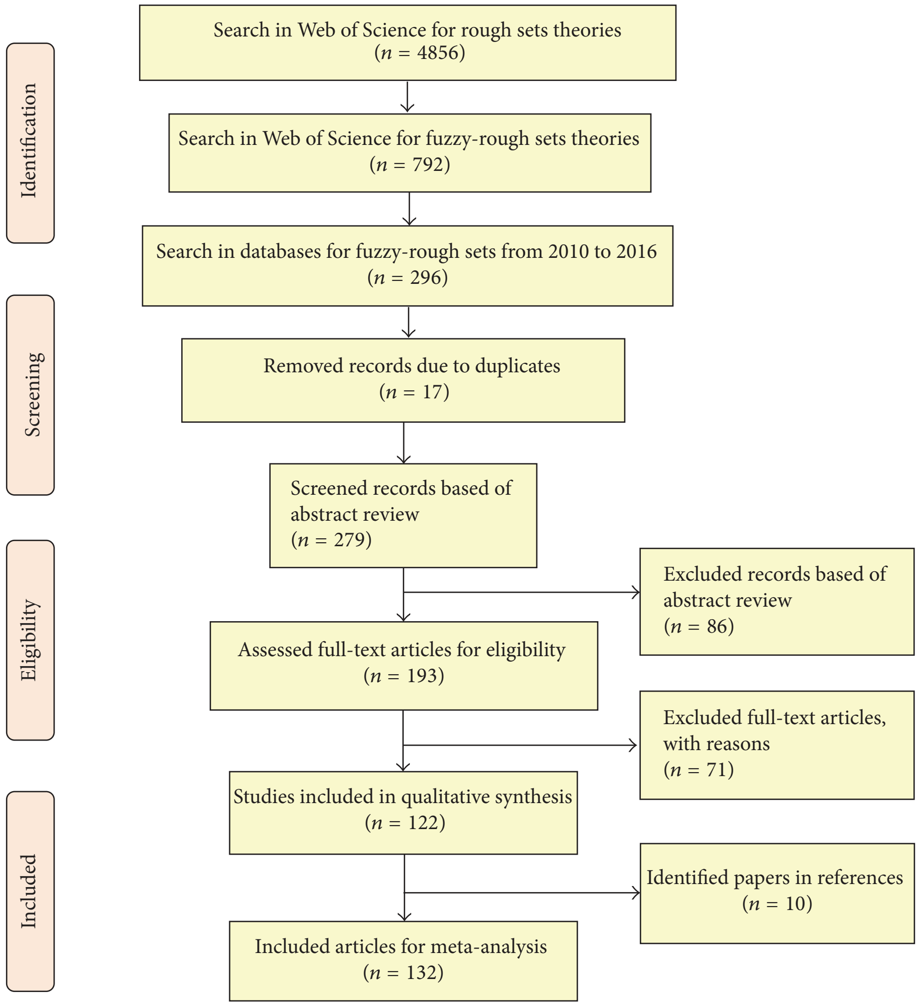


Figure 3: Study flowchart for the identification, screening, eligibility, and inclusion of articles.

Table 1: Classification of papers based on application area.

Application areas	Frequency	Percentage of frequency
Information systems	12	9.09%
Decision-making	9	8.33%
Approximation operators	15	11.36%
Feature and attribute selection	24	20.45%
Fuzzy set theories	37	27.27%
Other application areas	35	23.48%
Total	*132*	*100.00%*

articles were classified into different classifications including information systems, decision-making, approximate reasoning, feature and attribute selection, machine learning, fuzzy set theories, and other application areas. Also, the articles were summarised and reviewed based on the various criteria such as author and year of publication, author nationalities, application field, type of study, study category, study contribution, and journal in which they appeared. We believe that reviewing, summarising and classifying the articles helped us to achieve some critical and valuable insights. Consequently, some suggestions and recommendations for future studies were proposed. Furthermore, we believe that this review paper was accomplished very carefully and it presented a comprehensive source regarding the fuzzy-rough set theories. It should be noted that the main difficulty of using the PRISMA method was to understand what methodologies were used from the abstract and the research section of the selected articles. Thus, we required going through the full content of articles and took a more detailed look to evaluate the exactly applied approach to evaluate the fuzzy-rough sets. Although a considerable amount of time was spent in the selection process, it helped us choose the most suitable publications in conducting the review.

5. Application Areas Classification

Although categorising and combining the articles in the fields of fuzzy-rough sets is complex, for the classification task we used the opinions of experts. Consequently, based on opinions of experts we categorised articles into six different applications areas (see Table 1). In the following section, all selected articles were summarised and reviewed based on the various criteria.

5.1. Distribution Papers Based on Information Systems. Rough set theory is a powerful and popular machine learning method. It is particularly appropriate for dealing with the information systems that exhibit inconsistencies. Fuzzy set theory integrated with the rough set theory detects degrees of inconsistency in the data. Xu et al. [245] examined a new parallel attribute reduction algorithm by focusing on fuzzy-rough set theory and mutual information rather than calculating of the fuzzy-rough lower and upper approximations explicitly. Moreover, Yang et al. [246] investigated some rough sets models for handling big data, but this study does not focus on explicitly calculating the upper and lower approximations. Some previous scholars investigated the parallel models for computing the upper and lower approximations in the traditional rough set model. For example, Zhang et al. [247] introduced a new MapReduce-based approach for calculating the upper and lower approximations in a decision system. Zhang et al. [248] used different approximations to compare knowledge acquisition. Yang and Chen [249] suggested a novel approach to calculate the positive region such as the union of the lower approximation of all classes. Dubois and Prade [250] explored the relationship, similarities, and differences between twofold fuzzy sets and rough sets. Ouyang et al. [50] defined new fuzzy rough sets which generalized the concept of fuzzy rough sets in the sense of Radzikowska and Kerre [28], and that of Mi and Zhang [186]. Kuznetsov et al. [251] introduced an approach based on the fuzzy-rough sets which were called the (I, J)-fuzzy-rough set. Zeng et al. [52] developed a new Hybrid Distance (HD) in Hybrid Information System (HIS) based on the value difference metric, and a new fuzzy-rough approach was designed by integrating the Gaussian kernel and HD distance. Feng and Mi [39] investigated variable precision multigranulation fuzzy decision-theoretic rough sets in an information system. Chen et al. [55] introduced a new approach to build a polygonal rough-fuzzy set and presented a novel fuzzy interpolative reasoning approach for sparse fuzzy rule-based systems based on the ratio of fuzziness of the constructed polygonal rough-fuzzy sets. Table 2 represents significant distribution findings of information systems based on the author and year of publication, application field, type of study, study category, and study contribution. The results represented in this table indicate that 12 articles have been published in the area of information systems.

5.2. Distribution Papers Based on Decision-Making. While there are a variety of existing methods for various application areas from imprecise data, the fuzzy-rough set method has an advantage for decision-making for large volumes of data since it focuses on reducing the number of attributes required to characterize a concept without losing essential information required for decision-making. Although rough sets have several advantages over other methods, they generate a number of rules creating difficulties in decision-making [252]. A fuzzy-rough set is a data mining algorithm for decision-making based on incomplete, inconsistent, imprecise, and vague data. Fuzzy-rough set theory is an extension of the fuzzy conventional set theory that supports approximations in decision-making. However, rough set theories are valuable mathematical approaches for explaining and showing insufficient and incomplete information and also have been extensively used in numerous application areas such as comprehensive evaluation, and uncertainty decision-making with fuzzy information [62]. Greco et al. [253] proposed a new dominance rough set framework that is appropriate for preference analysis [31, 254–261]. This study investigated the decision-making problem with multicriteria and attributes, where dominance relations are extracted from similarity relations, and multicriteria are created from equivalence relations and numerical attributes are created from nominal attributes. An extensive review of multicriteria decision analysis based on dominance rough sets is given in Greco et al. [253]. Dominance rough sets have also been applied to ordinal attribute reduction [253, 262] and multicriteria classification [263–266]. Recently, several previous studies extended the fuzzy set based on the dominance rough set approach [106, 170, 258, 267, 268]. Hu et al. [60] proposed a novel approach for extracting the fuzzy preference relations by using a fuzzy-rough set model. Liang and Liu [61] presented a naive approach of intuitionistic fuzzy decision-theoretic rough sets (IFDTRSs) and analysed its related properties. Sun and Ma [65] introduced a novel concept of soft fuzzy-rough sets by integrating the traditional fuzzy-rough sets and fuzzy soft sets. The detailed results of this section are presented in Table 3. The findings represented in this table indicate that 8 articles have been published in the area of decision-making.

5.3. Distribution Papers Based on Approximation Operators. A rough set approximates a crisp set by two other sets that give a lower and upper approximation of the crisp set. In the rough set analysis, the data is expected to be discrete. In enormous information systems, the computation of the lower and upper approximation sets is a demanding process both regarding processing time and memory utilisation. A rough set approximates a certain set of elements with two other subsets called upper and lower approximations. Through the fuzzy-rough lower and upper approximation, fuzzy-rough set theory can model the quality or typicality of instances within their respective classes, and hence it is an ideal tool to detect border points and noisy instances. The lower approximation

Table 2: Distribution papers based on the information systems area.

Author and reference	Application field	Type of study	Study category	Study contribution
Liu and Sai [48]	Information systems	Developed	Fuzzy and rough sets	Discussed invertible upper and lower approximation and provided the sufficient and necessary condition for lower and upper approximation fuzzy-rough and rough sets
Zhang [49]	Information systems	Proposed	Fuzzy-rough sets	Proposed a new dominance intuitionistic fuzzy-rough set for using auditing risk judgment in information system security
Ouyang et al. [50]	Information systems	Developed	Fuzzy-rough sets	Generalised the Radzikowska and Kerre approach based on fuzzy-rough sets which were called the (I, J)-fuzzy-rough set
Dai and Tian [51]	Information systems	Proposed	Fuzzy-rough sets	Developed the fuzzy construct and relation of the fuzzy-rough approach for set-valued information systems
Zeng et al. [52]	Information systems	Developed	Fuzzy-rough sets	Developed a new Hybrid Distance (HD) in Hybrid Information Systems (HIS) based on the value difference metric, and a new fuzzy-rough approach was designed by integrating the Gaussian kernel and HD distance
Shabir and Shaheen [53]	Information system	Proposed	Fuzzy-rough sets	Suggested a novel framework for fuzzification of rough sets when the objects are α-indiscernible, that is, indiscernible up to a certain degree α
Feng and Mi [39]	Information systems	Developed	Fuzzy-rough sets	Investigated the variable precision multigranulation fuzzy decision-theoretic rough sets in an information system
Wu and Zhang [54]	Random fuzzy information systems	Proposed	Fuzzy-rough sets	Introduced new random fuzzy-rough set approaches based on fuzzy logic operators and random fuzzy sets
Chen et al. [55]	Fuzzy rule-based systems	Proposed	Fuzzy-rough sets	Introduced a new approach to build a polygonal rough-fuzzy set and present a novel fuzzy interpolative reasoning approach for sparse fuzzy rule-based systems based on the ratio of fuzziness of the constructed polygonal rough-fuzzy sets
Tsang et al. [56]	Information systems	Developed	Fuzzy-rough sets	Examined some properties of communication between information systems based on fuzzy-rough set models
Han et al. [57]	Decision information system	Proposed	Fuzzy-rough sets	Introduced the new order relation about bipolar-valued fuzzy sets
Aggarwal [58]	Fuzzy probabilistic information system	Developed	Fuzzy-rough sets	Developed probabilistic variable precision fuzzy-rough sets (P-VP-FRS)

Table 3: Distribution papers based on the decision-making area.

Author and reference	Application field	Type of study	Study category	Study contribution
Liang et al. [59]	Multiple attribute group decision-making (MAGDM)	Developed	Fuzzy-rough and triangular fuzzy sets	Designed a new algorithm for determination of the values of losses used in triangular fuzzy decision-theoretic rough sets (TFDTRS)
Hu et al. [60]	Decision-making	Proposed	Fuzzy preference and rough sets	Proposed a novel approach for extracting fuzzy preference relations by using a fuzzy-rough set model
Liang and Liu [61]	Information systems	Proposed	Fuzzy-rough sets	Presented a naive approach of IFDTRSs and analysis of its related properties
Sun et al. [62]	Decision-making	Proposed	Fuzzy-rough sets and emergency material demand prediction	Used fuzzy-rough sets for solving problems in emergency material demand prediction
Zhang et al. [63]	Decision-making	Proposed	Fuzzy-rough sets	Presented a common decision making model based on hesitant fuzzy and rough sets, named HF rough sets
Zhan and Zhu [64]	Decision-making	Proposed	Fuzzy-rough sets	Extended the new Z-soft rough fuzzy of hemirings based on the notion of soft rough sets and rough fuzzy sets
Sun and Ma [65]	Decision-making	Proposed	Fuzzy-rough sets	Introduced a novel concept of soft fuzzy-rough sets by integrating traditional fuzzy-rough sets and fuzzy soft sets
Yang et al. [66]	MCDM	Proposed	Fuzzy-rough sets	Introduced the concept of the union, the inverse of bipolar approximation spaces, and the intersection
Sun et al. [67]	Decision-making	Developed	Fuzzy-rough sets	Examined the fuzzy-rough approximation concept on i probabilistic approximation space over two universes

is the union of all cases that can be classified with certainty in one of the decision classes, whereas the upper approximation is a description of the instances that possibly belong to one of the decision classes. With the utilisation of rough set theory in the feature selection process, the vague concept can be modelled by the approximation of a vagueness set by a pair of precise concepts, called lower and upper approximations. The lower approximation, or positive region, is the union of all instances that can be classified with certainty in one of the decision values, whereas the upper approximation is a description of the instances that possibly belong to one of the decision values [269, 270]. Some previous papers investigated some properties of fuzzy-rough approximation operators. Hu et al. [60] proposed a novel approach for extracting the fuzzy preference relations by using a fuzzy-rough set model. Zhang et al. [63] presented a common decision-making model based on hesitant fuzzy and rough sets, named HF rough sets. Sun and Ma [65] introduced a novel concept of soft fuzzy-rough sets by integrating the traditional fuzzy-rough sets and fuzzy soft sets. Table 4 provides valuable distribution findings of approximation operators based on the author and year of publication, application field, type of study, study category, and study contribution. The results represented in this table indicate that 15 articles have been published in the area of approximation operators.

5.4. Distribution Papers Based on Feature or Attribute Selection. There are several other instances of information that can be derived from data, but in this section we focus on classification. Formally, given a dataset of instances described by conditional features and a decision feature, classifiers aim to predict the class of a new instance given its conditional features. Most classifiers first build a model based on the data and then feed the new instance to the model to predict its class. For example, Support Vector Machines (SVMs) [98, 271–273] construct a function that models a separating border between the different classes in the data, and the value of that function for the new instance then determines to what class it most likely belongs. Decision trees [274, 275] generate rules from the data following a tree structure that predict the class of a new instance. Zhu et al. [276] introduced a novel attribute reduction criterion for choosing lowest attributes while keeping the best performance of the corresponding learning algorithms to some extent. Inbarani et al. [277] proposed a new feature selection approach based on high dimensionality in the medical dataset. This classifier has no modelling phase. A new instance is classified directly by looking up the closest instances in the data and classifying it to the class mostly occurring among those nearest neighbors. Before the data can be used to build the classification model and to classify the new instances, the data needs to be preprocessed. For example, there can be missing values [278–281] in the data that need to be imputed. Preprocessing can also be used to speed up or improve the classification process. For example, fuzzy-rough feature selection techniques select features such that the membership degrees of the instances to the fuzzy-rough positive region are maximised [195], or instance selection techniques select instances with a high membership degree to the fuzzy-rough positive region [195]. Jensen et al. [83] proposed a model by using a rough set for solving the problems related to the propositional satisfiability perspective. Qian et al. [84] proposed an approach based on dimensionality reduction together with sample reduction for a heuristic process of fuzzy-rough feature selection. Derrac et al. [88] presented a new hybrid algorithm for reduction of data using feature and instance selection. Jensen and Mac Parthaláin [89] introduced two novel, diverse ways of using the attribute and neighborhood approximation step for solving problems of complexity of the subset evaluation metric. Maji and Garai [91] presented a new feature selection approach based on fuzzy-rough sets by maximising the significance and relevance of the selected features. Zeng et al. [52] developed a new Hybrid Distance (HD) in Hybrid Information System (HIS) based on the value difference metric, and a new fuzzy-rough approach by integrating the Gaussian kernel and HD distance. Cornelis et al. [95] introduced and extended a new rough set theory based on the multiadjoint fuzzy-rough sets for calculating the lower and upper approximations. Yao et al. [101] introduced a new fuzzy-rough approach called the variable precision (θ, σ) fuzzy-rough approach based on fuzzy granules. Zhao et al. [103] introduced a robust model for dimension reduction by using fuzzy-rough sets to achieve the possible parameters. Chen and Yang [104] integrated the rough set and fuzzy-rough set model for attribute reduction in decision systems with real and symbolic valued condition attributes. Table 5 provides valuable distribution findings of approximation operators based on the author and year of publication, application field, type of study, study category, and study contribution. The results represented in this table indicate that 23 articles have been published in the area of the attribute or attribute selection.

5.5. Distribution of Papers Based on Fuzzy Set Theories. In recent years, several studies have examined how rough set theory can be extended using various types of fuzzy set theories [53, 173, 238, 261, 282], which extends traditional set theory in the sense that instances can belong to a set to a certain degree between 0 and 1. Most studies have been conducted on fuzzy sets with fuzzy-rough sets [36, 81, 116, 125, 141, 283, 284], mainly focusing on preserving the predictive power of datasets with the least features possible. Some preliminary researches have been done on using fuzzy-rough set theory for instance selection [88] and its combination with fuzzy sets [120, 285]. Apart from using fuzzy-rough set theory for preprocessing, it has also been used successfully to tackle classification problems directly, for example, in rule induction [157, 170, 286, 287], decision-making [49, 59, 65, 288] improving K-NN classification [87, 289–293], interval-valued fuzzy sets [108, 122, 130, 133, 294, 295], enhancing decision trees [165, 296, 297], hesitant fuzzy sets [132, 133, 137, 173, 298], and boosting SVMs [11, 98] [25, 26, 68, 106]. Huang et al. [106] proposed Dominance Intuitionistic Fuzzy Decision Tables (DIFDT) based on the fuzzy-rough set approach. Zhang [109] proposed intuitionistic fuzzy-rough sets based on intuitionistic fuzzy coverings by using intuitionistic fuzzy triangular norms and intuitionistic fuzzy implication operators.

Table 4: Distribution papers based on approximation operators.

Author and reference	Application field	Type of study	Study category	Study contribution
Fan et al. [68]	Approximate reasoning	Proposed	Fuzzy-rough sets	Proposed a new dominance-based fuzzy-rough set model for decision analysis
Cheng [69]	Approximations	Proposed	Fuzzy-rough sets	Suggested two incremental approaches for fast computing of the rough fuzzy approximation including cut sets of fuzzy sets and boundary sets
Yang et al. [70]	Approximate reasoning	Proposed	Fuzzy probabilistic rough sets	Suggested a new fuzzy probabilistic rough set approach
Wu et al. [71]	Approximate reasoning	Proposed	Fuzzy-rough approximation	Examined the problem related to construct rough approximations of a vague set in fuzzy approximation space
Fan et al. [72]	Approximation reasoning	Proposed	Fuzzy-rough set and decision-theoretic rough sets	Proposed the quantitative decision-theoretic rough fuzzy set approaches based on logical disjunction and logical conjunction
Sun et al. [73]	Approximate reasoning	Developed	Rough set and fuzzy-rough sets	Proposed the upper and lower approximations of fuzzy sets based on a hybrid indiscernibility relation
Estaji et al. [74]	Approximate reasoning	Proposed	Fuzzy-rough sets	Introduced the notion of a θ-lower and θ-upper approximations of a fuzzy subset of L
Li and Yin [75]	Approximate reasoning	Proposed	Fuzzy-rough sets	Introduced a novel fuzzy algebraic structure which was a named TL-fuzzy-rough semigroup based on a T-upper fuzzy-rough approximation and ϑ-lower and operators
Zhang et al. [76]	Approximation operators	Developed	Fuzzy-rough sets	Discussed an approximation set of a vague set in Pawlak's approximation space
Li and Cui [77]	Approximation operators	Proposed	Fuzzy-rough sets	Introduced and investigated fuzzy topologies induced by fuzzy-rough approximation operators and the concept of similarity of fuzzy relations
Wu et al. [78]	Approximation operators	Developed	Fuzzy-rough sets	Investigated the axiomatic characterizations of relation-based (S, T)-fuzzy-rough approximation operators
Hao and Li [79]	L-fuzzy-rough approximation space	Developed	Fuzzy-rough sets	Discussed the relationship between L-topologies and L-fuzzy-rough sets in an arbitrary universe
Cheng [80]	Approximation	Proposed	Fuzzy-rough sets	Proposed two algorithms based on forward and backward approximations which were called mine rules based on the backward approximation and mine rules based on the forward approximation
Feng et al. [81]	Fuzzy approximation operators	Developed	Fuzzy-rough sets	Proposed the approximation of a soft set based on a Pawlak approximation space
Sun et al. [82]	Probabilistic rough fuzzy set	Proposed	Fuzzy-rough sets	Introduced a probabilistic rough fuzzy set using the conditional probability of a fuzzy event

Table 5: Distribution papers based on feature or attribute selection.

Author and reference	Application field	Type of study	Study category	Study contribution
Jensen et al. [83]	Feature selection	Proposed	Fuzzy-rough sets	Proposed a model by using rough sets for solving problems related to the propositional satisfiability perspective
Qian et al. [84]	Feature selection	Proposed	Fuzzy-rough feature selection	Proposed an approach based on dimensionality reduction together with sample reduction for a heuristic process of fuzzy-rough feature selection
Hu et al. [85]	Feature evaluation and selection	Developed	Fuzzy-rough sets	Proposed soft fuzzy-rough sets by developing rough sets to reduce the influence of noise
Hong et al. [86]	Machine learning	Proposed	Fuzzy-rough sets	Proposed the learning algorithm from the incomplete quantitative data sets based on rough sets
Onan [87]	Machine learning	Proposed	Fuzzy-rough sets	Introduced a new classification approach based on the fuzzy-rough nearest neighbor method for the selection of fuzzy-rough instances
Derrac et al. [88]	Feature selection	Proposed	Fuzzy-rough sets	Presented a new hybrid algorithm for reduction of data by using feature and instance selection
Jensen and Mac Parthaláin [89]	Feature selection	Proposed	Fuzzy-rough sets	Introduced two novel diverse ways by using an attribute and neighborhood approximation step for solving problems of complexity of the subset evaluation metric
Pal et al. [90]	Feature selection	Proposed	Fuzzy-rough sets	Proposed a new rough fuzzy approach for pattern classification based on granular computing
Zhang et al. [24]	Feature selection	Proposed	Fuzzy-rough sets	Proposed a new fuzzy-rough set based on information entropy for feature selection
Maji and Garai [91]	Feature selection	Developed	Fuzzy-rough sets	Presented a new feature selection approach based on fuzzy-rough sets by maximizing significant and relevance of the selected features
Ganivada et al. [92]	Feature selection	Proposed	Fuzzy-rough sets	Proposed the granular neural network for recognizing salient features of data, based on fuzzy sets and a fuzzy-rough set
Wang et al. [20]	Feature subset selection	Proposed	Fuzzy-rough sets	Proposed a new rough set approach for feature subset selection
Kumar et al. [93]	Feature selection	Proposed	Fuzzy-rough sets	Proposed a novel algorithm based on fuzzy-rough sets for future selection and classification of datasets with multifeatures
Hu et al. [94]	Feature selection	Proposed	Fuzzy-rough sets	Proposed two kinds of kernelized fuzzy-rough sets by integrating kernel functions and fuzzy-rough set approaches
Cornelis et al. [95]	Attribute selection	Developed	Fuzzy-rough sets	Introduced and extended a new rough set theory based on multiadjoint fuzzy-rough sets for calculating the lower and upper approximations

Table 5: Continued.

Author and reference	Application field	Type of study	Study category	Study contribution
Mac Parthaláin and Jensen [96]	Attribute reduction	Proposed	Fuzzy-rough sets	Presented various several unsupervised feature selection (FS) approaches based on fuzzy-rough sets
Dai and Xu [97]	Attribute selection	Proposed	Fuzzy-rough sets	Proposed the attribute selection method based on fuzzy-rough sets for tumor classification
Chen et al. [98]	Support vector machines (SVMs)	Developed	Fuzzy-rough sets	Improved the hard margin support vector machines based on fuzzy-rough sets and a training membership sample in the constraints
Hu et al. [99]	Support vector machine	Proposed	Fuzzy-rough sets	Proposed a novel approach for a fuzzy-rough model which was named soft fuzzy-rough sets for robust classification based on the approach
Wei et al. [100]	Attribute reduction	Proposed	Fuzzy-rough sets	Introduced two kinds of fuzzy-rough approximations and defined two corresponding relative positive region reducts
Yao et al. [101]	Attribute reduction	Proposed	Fuzzy-rough sets	Introduced a new expanded fuzzy-rough approach which was named the variable precision (θ, σ)-fuzzy-rough approach based on fuzzy granules
Chen et al. [102]	Attribute reduction	Developed	Fuzzy-rough sets	Developed a new algorithm for finding reduction based on the minimal factors in the discernibility matrix
Zhao et al. [103]	Attribute reduction	Proposed	Fuzzy-rough sets	Introduced the robust model of dimension reduction by using fuzzy-rough sets for (reflecting of the reducts) achieved on the possible parameters
Chen and Yang [104]	Attribute reduction	Developed	Fuzzy-rough sets	Integrating the rough set and fuzzy-rough set model for attribute reduction in decision systems with real and symbolic valued condition attributes

Zhang et al. [111] examined intuitionistic fuzzy-rough sets based on two universes, general binary relations, and an intuitionistic fuzzy implicator I and a pair (T, I) of the intuitionistic fuzzy t-norm T. Huang et al. [113] developed a novel multigranulation rough set which was named the Intuitionistic Fuzzy Multigranulation Rough Set (IFMGRS). Wang [114] examined type-2 fuzzy-rough sets based on extended t-norms and type 2 fuzzy relations in the convex normal fuzzy truth values. Chen et al. [117] introduced a geometrical interpretation and application of this type of membership functions. Ma [119] presented two novel types of fuzzy covering rough set for bridges linking covering rough sets and fuzzy-rough theory. Reference [29] investigated the topological characterizations of generalised fuzzy-rough regarding basic rough equalities. He et al. [120] proposed an inconsistent fuzzy decision system and reductions and improved discernibility matrix-based algorithms to discover reducts. Bai et al. [123] proposed an approach based on rough-fuzzy sets for the extraction of spatial fuzzy decision rules from spatial data that simultaneously were of two kinds of fuzziness, roughness and uncertainties. Zhao and Hu [124] examined the fuzzy and interval-valued Fuzzy Probabilistic Rough Sets within frameworks of fuzzy and interval-valued fuzzy probabilistic approximation spaces. Huang et al. [125] introduced an Intuitionistic Fuzzy (IF) graded approximation space based on IF graded neighborhood and discussed information entropy and rough entropy measures. Li et al. [299] integrated the interval type 2 fuzzy with rough set theory by using the axiomatic and constructive approaches. Khuman et al. [126] investigated the type 2 fuzzy sets and rough-fuzzy sets to provide a practical means to express complex uncertainty without the associated difficulty of a type 2 fuzzy set. Zhang [295] introduced a new model based on interval-valued rough intuitionistic fuzzy sets by integrating the classical Pawlak rough set and interval-valued IF set theory. Hu [130] developed an integrative model considering interval-valued fuzzy sets and variable precision named generalised interval-valued fuzzy variable precision rough sets. Yang et al. [132] investigated a novel fuzzy-rough set model based on constructive and axiomatic approaches to introduce the hesitant fuzzy-rough set model. Zhang et al. [133] integrated the interval-valued hesitant fuzzy sets with rough sets to introduce the novel model named the interval-valued hesitant fuzzy-rough set. Tiwari and Srivastava [300] investigated the results of some previous studies regarding the one-to-one correspondence between the family of fuzzy preorders on a nonempty set. Chen et al. [136] proposed a new rough-fuzzy approach for handling, representation, and utilisation of various levels of uncertainty in knowledge. Table 6 provides valuable distribution results of fuzzy sets theories based on the author and year of publication, application field, type of study, study category, and study contribution. The results represented in this table indicate that 37 articles have been published in the area of the attribute or attribute selection.

5.6. Distribution of Papers Based on Other Application Areas. In recent decades, rough sets and fuzzy-rough sets theories have been employed in various application areas such as data mining [4, 5, 86, 301–303], software packages [141, 304], web ontology [138, 305–307], pattern recognition [24, 148, 187, 308–310], granular computing [38, 221, 238, 251], genetic algorithm [310–313], prototype selection [145, 163], solid transportation [146, 314, 315], social networks [316–318], artificial neural network [92, 153, 319], remote sensing [320, 321], and gene selection [158, 322–324]. An et al. [140] analysed a regression algorithm based on fuzzy partition, fuzzy-rough sets, estimation of regression values, and fuzzy approximation for estimating wind speed. Shiraz et al. [142] proposed a new fuzzy-rough DEA approach by combining the classical DEA, rough set, and fuzzy set theory to accommodate the uncertainty. Zhou et al. [144] developed a new approach for automatic selection of the threshold parameter to determine the approximation regions in rough set-based clustering. Vluymans et al. [19] introduced a novel kind of classifier for imbalanced multi-instance data based on fuzzy-rough set theory. Ganivada et al. [150] proposed a Fuzzy-Rough Granular Self-Organising Map (FRGSOM) by including the three-dimensional linguistic vector and connection weights for clustering the patterns which included overlapping regions. Amiri and Jensen [151] introduced three missing imputation approaches based on the fuzzy-rough nearest neighbors, namely, VQNNI, OWANNI, and FRNNI. Feng and Mi [39] introduced the use of data mining approaches to forecast the need of maintenance. Affonso et al. [153] proposed a new method for biological image classification by a rough-fuzzy artificial neural network. Pahlavani et al. [155] proposed a novel fuzzy-rough set model to extract the rules in the ANFIS based classification procedure for choosing the optimum features. Zhao et al. [157] developed a rule-based classifier fuzzy-rough using one generalised fuzzy-rough set model to introduce a novel idea which was called consistence degree. Maji and Pal [158] presented a new fuzzy equivalence partition matrix for approximating the true marginal and joint distributions of continuous gene expression values. Huang and Kuo [159] investigated two perspectives of cross-lingual semantic document similarity measures based on the fuzzy sets and rough sets which were named formulation of similarity measures and document representation. Ramentol et al. [161] developed a learning algorithm for considering the imbalance representation and proposed a classification algorithm for imbalanced data by using the fuzzy-rough sets and ordered weighted average aggregation. Derrac et al. [163] introduced a new fuzzy-rough set model for prototype selection by optimising the behaviour of this classifier. Zhao et al. [166] introduced a novel complement information entropy method in the fuzzy-rough sets based on the arbitrary fuzzy relations, inner-class, and outer-class information. Changdar et al. [168] presented a new genetic-ant colony optimisation algorithm in a fuzzy-rough set environment for solving problems related to the solid multiple Travelling Salesmen Problem (mTSP). Sun and Ma [169] introduced a novel model to evaluate the emergency plants for unconventional emergency events using soft fuzzy-rough set theory. The results of this section are provided in Table 7.

Table 6: Distribution papers based on fuzzy set theories.

Author and reference	Application field	Type of study	Study category	Study contribution
Gong and Zhang [105]	Fuzzy system	Proposed	Rough sets	Suggested a novel extension of the rough set theory by integrating precision rough set theory variables and intuitionistic fuzzy-rough set theory
Huang et al. [106]	Intuitionistic fuzzy	Proposed	Rough sets and intuitionistic fuzzy sets	Proposed dominance intuitionistic fuzzy decision tables (DIFDT) based on a fuzzy-rough set approach
Pawlak [3]	Type 2 fuzzy	Proposed	Interval type 2 fuzzy and rough sets	Integrated the interval type 2 fuzzy sets with rough set theory by using the axiomatic and constructive approaches
Yang and Hinde [107]	Fuzzy set	Proposed	Fuzzy set and R-fuzzy sets	Suggested a new extension of fuzzy sets which was called R-fuzzy sets as an element of rough sets
Cheng et al. [108]	Interval-valued fuzzy	Developed	Interval-valued fuzzy-rough sets	Proposed two new algorithms based on converse and positive approximations which were named MRBPA and MRBCA
Zhang [109]	Intuitionistic fuzzy	Proposed	Fuzzy-rough sets and intuitionistic fuzzy sets	Proposed intuitionistic fuzzy-rough sets based on intuitionistic fuzzy coverings using intuitionistic fuzzy triangular norms and intuitionistic fuzzy implication operators
Xue et al. [110]	Fuzzy-rough C-means clustering	Proposed	Fuzzy-rough sets	Proposed a new fuzzy-rough semisupervised outlier detection (FRSSOD) method for helping some fuzzy-rough C-means clustering and labelled samples
Zhang et al. [111]	Intuitionistic fuzzy	Developed	Intuitionistic fuzzy-rough sets	Examined the intuitionistic fuzzy-rough sets based on two universes, general binary relations, and an intuitionistic fuzzy implicator I and a pair (T, I) of the intuitionistic fuzzy t-norm T
Wei et al. [112]	Fuzzy entropy	Developed	Fuzzy-rough sets	Analyzed and evaluated the roughness of a rough set based on fuzzy entropy measures
Wang and Hu [40]	L-fuzzy-rough sets	Proposed	Fuzzy-rough sets	Introduced the generalised L-fuzzy-rough set for more generalisation of the notion of L-fuzzy-rough set
Huang et al. [113]	Intuitionistic fuzzy	Developed	Fuzzy-rough sets	Developed a novel a new multigranulation rough set which was named the intuitionistic fuzzy multi-granulation rough set (IFMGRS)
Wang [114]	Type 2 fuzzy sets	Developed	Fuzzy-rough sets	Examined type 2 fuzzy-rough sets based on extended t-norms and type 2 fuzzy relations in the convex normal fuzzy truth values
Yang and Hu [115]	Fuzzy β-covering	Developed	Fuzzy-rough sets	Examined the new fuzzy covering-based rough approach by defining the notion of a fuzzy β-minimal description
Lu et al. [116]	Type 2 fuzzy	Developed	Fuzzy-rough sets	Defined type 2 fuzzy-rough sets based on a wavy-slice representation of type 2 fuzzy sets
Chen et al. [117]	Fuzzy similarity relation	Proposed	Fuzzy-rough sets	Introduced the geometrical interpretation and application of this type of membership functions

Table 6: Continued.

Author and reference	Application field	Type of study	Study category	Study contribution
D'eer et al. [118]	Fuzzy relations	Reviewed	Fuzzy-rough sets	Assessed the most important fuzzy-rough approaches based on the literature
Wang and Hu [38]	Fuzzy granules	Proposed	Fuzzy-rough sets	Proposed the variable precision (θ, σ)-fuzzy-rough set to remedy the defects of preexisting fuzzy-rough set approaches
Ma [119]	Fuzzy β-covering	Developed	Fuzzy-rough sets	Presented two novel kinds of fuzzy covering rough set approaches for bridges linking covering rough sets and fuzzy-rough theory
Wang [29]	Fuzzy topology	Developed	Fuzzy-rough sets	Investigated the topological characterizations of generalised fuzzy-rough sets regarding basic rough equalities
He et al. [120]	Fuzzy decision system	Proposed	Fuzzy-rough sets	Proposed the inconsistent fuzzy decision system and reductions and improved discernibility matrix-based algorithms to discover reducts
Yang et al. [121]	Bipolar fuzzy sets	Developed	Fuzzy-rough sets	Generalized the fuzzy-rough approach based on two different universes introduced by Sun and Ma
Zhang [122]	Interval type 2	Proposed	Fuzzy-rough sets	Suggested a new model for interval type 2 rough fuzzy sets by employing constructive and axiomatic methods
Bai et al. [123]	Fuzzy decision rules	Proposed	Fuzzy-rough sets	Proposed an approach based on rough fuzzy sets for the extraction of spatial fuzzy decision rules from spatial data that simultaneously were two kinds of fuzziness, roughness, and uncertainties
Zhao and Hu [124]	Interval-valued fuzzy probabilistic	Developed	Fuzzy-rough sets	Examined the fuzzy and interval-valued fuzzy probabilistic rough sets within frameworks of fuzzy and interval-valued fuzzy probabilistic approximation spaces
Huang et al. [125]	Intuitionistic fuzzy-rough sets	Proposed	Fuzzy-rough sets	Introduced the intuitionistic fuzzy (IF) graded approximation space based on the IF graded neighborhood and discussed information entropy and rough entropy measures
Khuman et al. [126]	Type 2 fuzzy set	Developed	Fuzzy-rough sets	Investigated the type 2 fuzzy sets and rough fuzzy sets to provide a practical means to express complex uncertainty without the associated difficulty of a type 2 fuzzy set
Liu and Lin [127]	Intuitionistic fuzzy-rough	Proposed	Fuzzy-rough sets	Proposed a new intuitionistic fuzzy-rough approach based on the conflict distance
Sun et al. [128]	Interval-valued rough intuitionistic fuzzy	Proposed	Fuzzy-rough sets	Proposed a new framework based on intuitionistic fuzzy-rough sets with the constructive approach
Zhang et al. [129]	Hesitant fuzzy	Proposed	Fuzzy-rough sets	Proposed the common model based on rough set theory and dual hesitant fuzzy sets named dual hesitant fuzzy-rough sets by consideration of constructive and axiomatic models
Hu [130]	Interval-valued fuzzy	Developed	Fuzzy-rough sets	Generalized to an integrative model based on considering interval-valued fuzzy sets and variable precision sets named generalized interval-valued fuzzy variable precision rough sets

Table 6: Continued.

Author and reference	Application field	Type of study	Study category	Study contribution
Zhao and Xiao [131]	General type 2 fuzzy sets	Proposed	Fuzzy-rough sets	Proposed a novel model by integrating general type 2 fuzzy sets, rough sets, and the α-plane representation method
Yang et al. [132]	Hesitant fuzzy set	Proposed	Fuzzy-rough sets	Investigated a novel fuzzy-rough model based on constructive and axiomatic approaches to introduce the hesitant fuzzy-rough set model
Zhang et al. [133]	Interval-valued hesitant fuzzy set	Proposed	Fuzzy-rough sets	Integrated interval-valued hesitant fuzzy sets with rough sets to introduce a novel model named the interval-valued hesitant fuzzy-rough set
Wang and Hu [134]	Fuzzy-valued operations	Developed	Fuzzy-rough sets	Examined the fuzzy-valued operations and the lattice structures of the algebra of fuzzy values
Zhao and Hu [36]	IVF probability	Developed	Fuzzy-rough sets	Examined the decision-theoretic rough set (DTRS) method based on fuzzy and interval-valued fuzzy (IVF) probabilistic approximation spaces
Mitra et al. [135]	Fuzzy clustering	Developed	Fuzzy-rough sets	Developed shadowed sets by combining fuzzy and rough clustering
Chen et al. [136]	Fuzzy rule interpolation	Proposed	Fuzzy-rough sets	Proposed a new rough fuzzy approach for handling, representation and utilisation of diverse levels of uncertainty in knowledge

6. Distribution of Reviewed Paper by Journals

Table 8 presents the results of analysing the articles based on distribution of the journals. The articles related to the fuzzy-rough set theory have been chosen from 28 different international scholarly journals indexed in the Web of Science databases. Selected articles published, along with an extensive diversity of journals that focus on fuzzy-rough set theory, validate different scholarly journals willingness to publish in this field. By far, the highest ranking journal is the journal of Information Sciences with 36 articles, followed by the journal of Fuzzy sets and Systems with 17 papers. Furthermore, more than 60 percent of the total papers (83 out of 132 papers) were concentrated in five journals, which play dominant roles in field of rough-fuzzy set theory. Additionally, in other rankings, the Soft Computing journal had the third rank with 11 publications followed by journal of Knowledge-Based Systems and IEEE Transactions on Fuzzy Systems with 10 articles. Hence, based on this result, we can conclude that these selected journals can be considered as the main journals on the fuzzy-rough set theory, as the more than 60 percent of the articles were published in these journals. Table 8 presents the list of journals where the fuzzy-rough set theory has been published.

7. Distribution of Articles by Year of Publication

In recent decades, the application of fuzzy-rough set theory has increased dramatically in the literature. A historical growth of fuzzy-rough sets has existed for many years. A frequency analysis of the 132 articles based on the articles published for different years is shown in Figure 4. During 2010–2012, the articles published on fuzzy-rough set theory were at a steady rate with 15, 11, and 15 articles. The uptrend in papers outputs is observed since the year 2012, until 2016. Figure 4 presents relevant information based on the frequency of distribution by the year of publication. Accordingly, it can be indicated that nowadays researchers are highly interested in conducting research on fuzzy-rough set theory and it can be predicted that in coming years these numbers will increase.

8. Distribution of Papers Based on Nationality of Authors

This review paper attempted to show the difference among the countries related to the fuzzy-rough set theory. Two kinds of principles were used for identifying the characteristics in selected articles, including the information gained directly from the papers or the nationality of the first author. Figure 5 shows that authors from 16 nationalities and countries investigated the fuzzy-rough set theory. Most of the published papers were from China with 86 publications followed by India, United Kingdom, and Spain with 13, 6, and 5 publications, respectively. Figure 5 shows the frequency of other nationalities, as well.

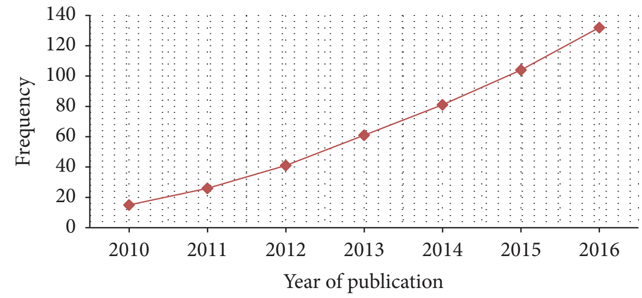


Figure 4: Distribution of articles by year of publication.

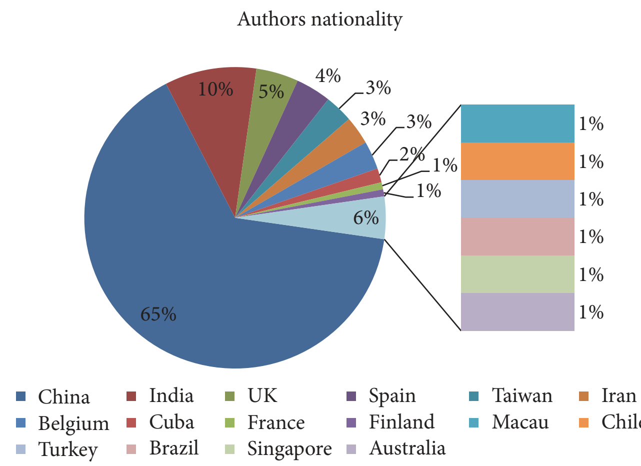


Figure 5: Distribution of papers based on nationality of authors.

9. Discussion

There are some challenges regarding various application areas of fuzzy-rough set theory that can be interesting for discussion and future studies. For example, in the case of fuzzy β-covering approximation spaces, there are various topics which need further research, such as matroidal structures, data mining, the generalisation of fuzzy covering-based rough sets, topological properties and data compression with homomorphism, and communication by using fuzzy covering-based rough sets. In the area of multigranulation fuzzy-rough set theory, some more investigations are needed. For example, it is necessary to explore the primary theory and characterizations of multigranulation fuzzy-rough sets over two universes, as well as attribute reduction of the multigranulation fuzzy approximation space over two universes. In the field of fuzzy information system over Two Universes (ISTU), further study is necessary to enhance the current incremental algorithms by integration with the parallelism technique to update rough approximations. More investigations are required in the area of interval-valued hesitant fuzzy multigranulation rough sets over two universes, to study uncertainty measures, topological structures, and attribute reduction methods. Also, further investigations are needed in the area of the Dominance-Based Fuzzy-Rough Set Approach (DFRSA), by improving the attribute reduction, rule induction, and object reduction. In the field of fuzzy

Table 7: Distribution papers based on other application areas.

Author and reference	Application field	Type of study	Study category	Study contribution
Zhang et al. [137]	Pattern recognition	Developed	Fuzzy and rough sets	Presented a novel rough set model by integrating multigranulation rough sets over two universes and interval-valued hesitant fuzzy sets which is called interval-valued hesitant fuzzy multigranulation rough sets
Bobillo and Straccia [138]	Web ontology	Proposed	Fuzzy-rough sets	Presented a solution related to fuzzy DLs and rough DLs which is called fuzzy-rough DL
Liu [139]	Axiomatic approaches	Developed	Fuzzy-rough sets	Investigated the fixed universal set U where, unless otherwise stated, the cardinality of U is infinite
An et al. [140]	Fuzzy-rough regression	Developed	Fuzzy-rough sets	Analyzed the regression algorithm based on fuzzy partition, fuzzy-rough sets, estimation of regression values, and fuzzy approximation for estimating wind speed
Riza et al. [141]	Software packages	Developed	Fuzzy-rough sets	Implementing and developing fuzzy-rough set theory and rough set theory algorithms in the *R* package
Shiraz et al. [142]	Fuzzy-rough DEA	Proposed	Fuzzy-rough sets	Proposed a new fuzzy-rough DEA approach by combining the classical DEA, rough set, and fuzzy set theory to accommodate for uncertainty
Saltos and Weber [11]	Data mining	Proposed	Fuzzy-rough sets	Introduced a new soft clustering model based on support vector clustering
Zeng et al. [143]	Big data	Developed	Fuzzy-rough sets	Analyzed the changing mechanisms of the attribute values and fuzzy equivalence relations in fuzzy-rough sets
Zhou et al. [144]	Rough set-based clustering	Developed	Fuzzy-rough sets	Developed a new approach for automatic selection of the threshold parameter for determining the approximation regions in rough set-based clustering
Verbiest et al. [145]	Prototype selection	Proposed	Fuzzy-rough sets	Introduced the prototype selection model based on fuzzy-rough sets
Vluymans et al. [19]	Multi-instance learning	Proposed	Fuzzy-rough sets	Introduced a novel kind of classifier for imbalanced multi-instance data based on fuzzy-rough set theory
Pramanik et al. [146]	Solid transportation	Developed	Fuzzy-rough sets	Developed biobjective fuzzy-rough expected value approaches
Liu [147]	Binary relation	Developed	Fuzzy-rough sets	Defined the concept of a solitary set for any binary relation from U to V
Meher [148]	Pattern classification	Developed	Fuzzy-rough sets	Developed the new rough fuzzy pattern classification approach by combining the merits of fuzzy and rough sets
Kundu and Pal [149]	Social networks	Proposed	Fuzzy-rough sets	Proposed a new community detection algorithm to identify fuzzy-rough communities
Ganivada et al. [150]	Granular computing	Proposed	Fuzzy-rough sets	Proposed the fuzzy-rough granular self-organizing map (FRGSOM), including the three-dimensional linguistic vector and connection weights for clustering patterns having overlapping regions
Amiri and Jensen [151]	Missing data imputation	Proposed	Fuzzy-rough sets	Introduced three missing imputation approaches based on fuzzy-rough nearest neighbors, namely, VQNNI, OWANNI and FRNNI

Table 7: Continued.

Author and reference	Application field	Type of study	Study category	Study contribution
Ramentol et al. [152]	Fuzzy-rough imbalanced learning	Proposed	Fuzzy-rough sets	Introduced the use of data mining approaches in order to forecast the need of maintenance
Affonso et al. [153]	Artificial neural network	Proposed	Fuzzy-rough sets	Proposed a new method for biological image classification by a rough-fuzzy artificial neural network
Shukla and Kiridena [154]	Dynamic supply chain	Developed	Fuzzy-rough sets	Developed a new framework based on fuzzy-rough sets for configuring supply chain networks
Pahlavani et al. [155]	Remote Sensing	Proposed	Fuzzy-rough sets	Proposed a novel fuzzy-rough set model to extract rules in the ANFIS based classification procedure for choosing the optimum features
Xie and Hu [156]	Fuzzy-rough set	Proposed	Fuzzy-rough sets	Introduced a novel extended model based on three kinds of fuzzy-rough sets and two universes
Zhao et al. [157]	Constructing classifier	Developed	Fuzzy-rough sets	Developed a rule-based classifier fuzzy-rough using one generalized fuzzy-rough model to introduce a novel idea which was called consistence degree
Maji and Pal [158]	Gene selection	Proposed	Fuzzy-rough sets	Presented a new fuzzy equivalence partition matrix for approximating of the true marginal and joint distributions of continuous gene expression values
Huang and Kuo [159]	Cross-lingual	Developed	Fuzzy-rough sets	Investigated two perspectives of cross-lingual semantic document similarity measures based on fuzzy sets and rough sets which was named formulation of similarity measures and document representation
Wang et al. [160]	Active learning	Proposed	Fuzzy-rough sets	Proposed a new fuzzy-rough set approach for the sample's inconsistency between decision labels and conditional features
Ramentol et al. [161]	Imbalanced classification	Proposed	Fuzzy-rough sets	Developed a learning algorithm for considering the imbalance representation and proposed a classification algorithm for imbalanced data by using fuzzy-rough sets and ordered weighted average aggregation
Zhang et al. [162]	Parallel disassembly sequence planning	Proposed	Fuzzy-rough sets	Proposed a new parallel disassembly sequence planning based on fuzzy-rough sets to reduce time complexity
Derrac et al. [163]	Prototype selection	Proposed	Fuzzy-rough sets	Introduced a new fuzzy-rough set model for prototype selection based on optimizing the behavior of this classifier
Verbiest et al. [164]	Prototype selection	Proposed	Fuzzy-rough sets	Improved The Synthetic Minority Over-Sampling Technique (SMOTE) to balance imbalanced data and proposed two prototype selection approaches based on fuzzy-rough sets
Zhai [165]	Fuzzy decision trees	Proposed	Fuzzy-rough sets	Proposed new expanded attributes using significance of fuzzy conditional attributes with respect to fuzzy decision attributes
Zhao et al. [166]	Uncertainty measure	Proposed	Fuzzy-rough sets	Introduced a novel complement information entropy method in fuzzy-rough sets based on arbitrary fuzzy relations, inner-class and outer-class information
Hu et al. [167]	Fuzzy-rough set	Developed	Fuzzy-rough sets	Examined the properties of some existing fuzzy-rough sets in dealing with noisy data and proposed various robust approaches

Table 7: Continued.

Author and reference	Application field	Type of study	Study category	Study contribution
Changdar et al. [168]	Genetic algorithm	Proposed	Fuzzy-rough sets	Presented a new genetic-ant colony optimization algorithm in a fuzzy-rough set environment for solving problems related to the solid multiple Travelling Salesmen Problem (mTSP)
Sun and Ma [169]	Emergency plans evaluation	Proposed	Fuzzy-rough sets	Introduced a novel model to evaluate emergency plans for unconventional emergency events using soft fuzzy-rough set theory

Table 8: Distribution of papers based on the name of journals.

Name of journals	Frequently	Percentage
Information Sciences	36	27.27%
Fuzzy sets and Systems	15	11.36%
Soft Computing	11	8.33%
Knowledge-Based Systems	10	7.58%
IEEE Transactions On Fuzzy Systems	10	7.58%
Pattern Recognition	6	4.55%
International Journal of General Systems	5	3.79%
Journal of Approximate Reasoning	5	3.79%
Expert Systems with Applications	5	3.79%
Applied Soft Computing	5	3.79%
Applied Mathematical Modelling	4	3.03%
Pattern Recognition Letters	2	1.52%
IEEE Transactions on Knowledge and Data Engineering	2	1.52%
Neurocomputing	2	1.52%
Artificial Intelligence Review	1	0.76%
Expert Systems	1	0.76%
Data & Knowledge Engineering	1	0.76%
Neural Networks	1	0.76%
Mathematics and Computers in Simulation	1	0.76%
Fundamenta Informaticae	1	0.76%
Socio-Economic Planning Sciences	1	0.76%
Theoretical Computer Science	1	0.76%
Engineering Applications of Artificial Intelligence	1	0.76%
International Journal of Production Research	1	0.76%
International Journal of Remote Sensing	1	0.76%
The International Journal of Advanced Manufacturing Technology	1	0.76%
Kybernetes	1	0.76%
Mathematics and Computers in Simulation	1	0.76%
Total	*132*	*100.00%*

neighborhood rough sets, further study is necessary regarding classification learning and reasoning with uncertainty. In addition, in the area of type 2 fuzzy-rough sets, further investigations are required regarding attribute reduction related to granular type 2 fuzzy sets and various methods of knowledge discovery in the complex fuzzy information systems. Furthermore, although some studies have investigated type-2 variable precision multigranulation fuzzy-rough sets, future studies can focus on uncertainty and reduction measures of variable precision multigranulation fuzzy-rough sets. Moreover, although some scholars have examined Fuzzy Probabilistic Rough Sets (FPRSs) and Interval-Valued Fuzzy Probabilistic Rough Sets (IVF-PRSs) with models of IVF and fuzzy probabilistic approximation spaces, there is still need to focus on characterizations of axiomatic methods in FPRSs and IVF-PRSs models. Although some previous papers investigated Gaussian Kernel Fuzzy-Rough Sets (FRS) in Hybrid Information Systems (HIS) further studies are required regarding technologies of parallel computing, for example, Map Reduce to optimise the increment updating model. There are also some papers regarding intuitionistic fuzzy-rough set model. However, more investigation is necessary to improve and construct the dominance intuitionistic fuzzy variable precision rough sets theory models. Although some previous papers examined the DTRS approach in the area of fuzzy and IVF probabilistic approximation spaces, there is a need for more studies to be conducted on the circumstance of IVF sets. In addition, there are some works related to IFDTRSs focusing on decision-theoretic rough sets; nonetheless, there is a need for more investigations on generalisation models based on the IFDTRSs. Although some previous researchers focused on the fuzzy topologies induced by the fuzzy-rough approximation operators, further articles are necessary for enhancing the generalised similarity of fuzzy relations, based on the t-norms and complete residuated lattices. Furthermore, although papers were published regarding the Intuitionistic Fuzzy Multigranulation Rough Sets (IFMGRS), further enhancements of these models are required by focusing on an interval-valued IF environment.

10. Conclusion

This review paper presented a comprehensive overview of recent fuzzy generations of rough sets theory in various applications areas. In total, 132 papers were selected for systematic review and meta-analysis in the period 2010–2016 from popular international journals accessible in the Web of Science database. We carefully selected and reviewed 132 studies about the fuzzy-rough set theory based on the title, abstract, introduction, research methods, and conclusions. These selected papers were categorised into six application areas. Also, all papers were classified based on the author and year of publication, author nationalities, application field, type of study, study category, study contribution, and journal in which they appeared. Some points on fuzzy-rough set theory were gained from this review article. The vast majority of reviewed articles were published between 2013 and 2016. In total, the papers were classified into six areas including information systems, decision-making, approximation operators, feature and attribute selection, fuzzy set theories, and other application areas. Fuzzy set theory combined with rough set theory was the most important application area with 37 papers. Furthermore, 28 international peer reviewed journals were considered in the current review paper. The Journal of Information Systems had the first rank among the considered journals regarding publishing papers related to the fuzzy-rough set theory. The articles published at the beginning of 2017 (if any) have not been included in the present paper because of the limited reporting time. We attempted to use those published articles in other sections of our review paper, such as related works and introduction sections. However, this present review can be developed for the future studies. Another limitation is that the data was collected from journals, while the examined documents did not include textbooks, doctoral and master's theses, and unpublished papers on MCDM problems. Although we attempted to provide the comprehensive review based on the current and old literature, nevertheless, as a recommendation for future studies, the data can be collected from these sources, and the obtained results can be compared with the data obtained and reported in this study. Another limitation of this review was that all of the papers were extracted from the journals written in English. Hence, scientific journals in other languages were not included in the review. However, the researchers believe that this paper comprehensively reviewed most of the papers published in international journals. In this paper, we reviewed 132 papers which recently studied generalised fuzzy-rough sets theory but attempted to include the comprehensive list of papers in other sections. In addition, we carefully selected and summarised the available papers of several publishers in the Web of Science database. However, some relevant outlets remained beyond the scope of the current study. Therefore, future researchers will be able to review those papers which are not considered in the current review. Another limitation of the survey is that although the paper presents various journals and conference publications that recently studied generalised fuzzy-rough set models, it does not include any of this topic discussed in the published books.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of the paper.

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